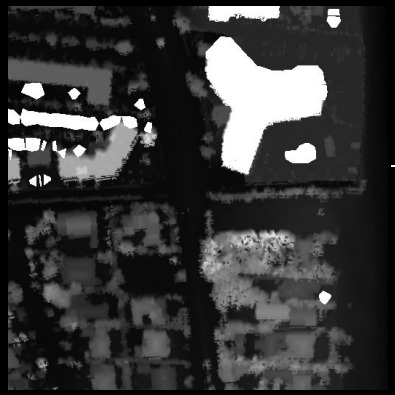
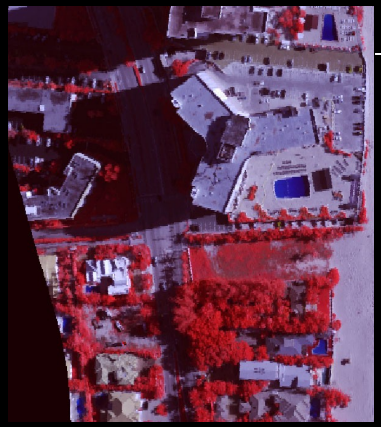
NOPP Status Report

George Raber
Department of Geography and Geology
The University of Southern Mississippi

Method Overview



Topo LIDAR Processed to DSM



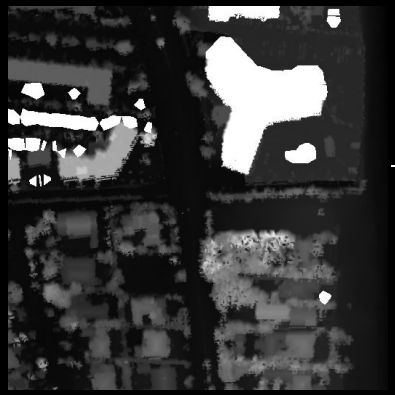
Hyperspectral Dataset (corrected reflectance)

Bathy LIDAR Processed to DSM

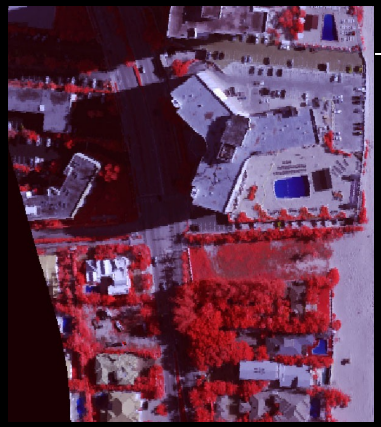
Segments Attributed with LIDAR metrics

Segmented Data

Method Overview



Topo LIDAR Processed to DSM



Hyperspectral Dataset (corrected reflectance)

Bathy LIDAR Processed to DSM

Segments Attributed with LIDAR metrics

Segmented Data

Method Overview

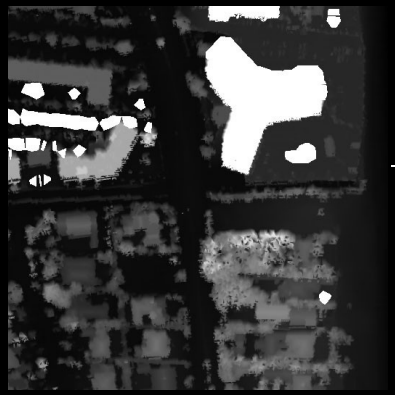
Segmented Data

A number of segmentation algorithms have been tested.

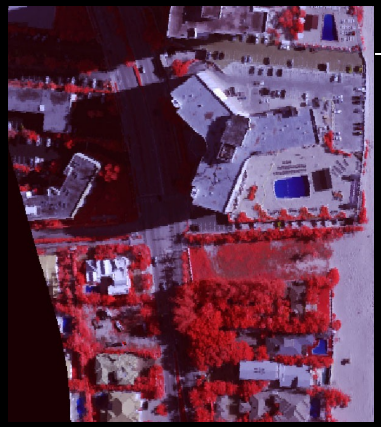
- Spectral Approaches
  - ISODATA
  - K-MEAN
- Spectral / Spatial Approaches
  - eCognition (a commercial product - Definiens)
  - Mean Shift Algorithm (developed by Robust Image Understanding Laboratory at Rutgers University)

Each approach demonstrated some effectiveness, but the examples are shown using the mean shift algorithm (this has not yet been programmed into ENVI, however the algorithm is

Method Overview



Topo LIDAR Processed to DSM



Hyperspectral Dataset (corrected reflectance)

Bathy LIDAR Processed to DSM

Segments Attributed with LIDAR metrics

Segmented Data

Method Overview

Segments Attributed with LIDAR metrics

Current List of Segment Attributes

Attribute	Description
Shape Statistics	Area, Perimeter, Compactness, Fractal Dimension
LIDAR Basic Statistics	Mean, Median, Range, Portions of the Mean and Range (e.g. 10% to 90%), Standard Deviation, Skewness, Kurtosis
LIDAR Vertical Distribution Statistics	Vertical Histogram of Z values, Cumulative histogram normalized to 1.
LIDAR Spatial Autocorrelation Statistics	Empirical Semi-variance calculated at a number of different lag values.
LIDAR Curve fit Statistics	The residual is calculated for fitting a 1^{st} – 5^{th} order polynomial curve through the segments z values.
Hyperspectal Data Statistics	Mean, Range and Mean of the middle 80% of the data are calculated.

Method Overview

Segments Attributed with LIDAR metrics

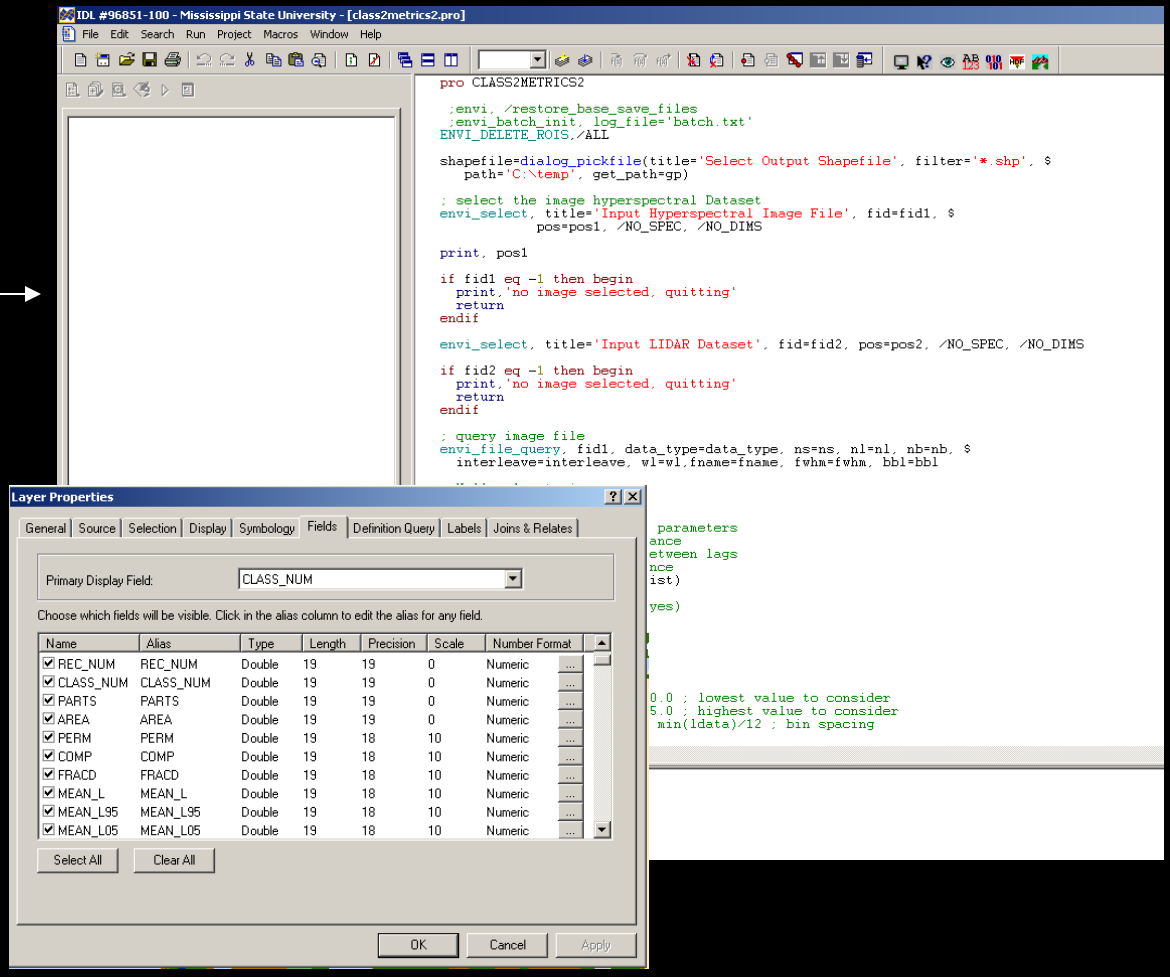
The attribution of the segments is completely automated and coded in IDL and ~~runs in ENVI~~

The user is prompted to select the following inputs:

- *The Hyperspectral Image*
- *The LIDAR DSM*
- *The Classified Image (Segments)*

• The Output is an ~~ESRI~~ shape file with the attributes as fields.

Segment Attributes


IDL #96851-100 - Mississippi State University - [class2metrics2.pro]
File Edit Search Run Project Macros Window Help
pro CLASS2METRICS2
;envi, /restore_base_save_files
;envi_batch_init, log_file='batch.txt'
ENVI_DELETE_ROIS,/ALL
shapefile=dialog_pickfile(title='Select Output Shapefile', filter='*.shp', $
path='C:\temp', get_path=gp)
; select the image hyperspectral Dataset
envi_select, title='Input Hyperspectral Image File', fid=fid1, $
pos=pos1, /NO_SPEC, /NO_DIMS
print, pos1
if fid1 eq -1 then begin
print,'no image selected, quitting'
return
endif
envi_select, title='Input LIDAR Dataset', fid=fid2, pos=pos2, /NO_SPEC, /NO_DIMS
if fid2 eq -1 then begin
print,'no image selected, quitting'
return
endif
; query image file
envi_file_query, fid1, data_type=data_type, ns=ns, nl=nl, nb=nb, $
interleave=interleave, wl=wl,fname=fname, fwhm=fwhm, bbl=bbl
Layer Properties
General Source Selection Display Symbology Fields Definition Query Labels Joins & Relates
Primary Display Field: CLASS_NUM
Choose which fields will be visible. Click in the alias column to edit the alias for any field.
Name Alias Type Length Precision Scale Number Format
REC_NUM REC_NUM Double 19 19 0 Numeric
CLASS_NUM CLASS_NUM Double 19 19 0 Numeric
PARTS PARTS Double 19 19 0 Numeric
AREA AREA Double 19 19 0 Numeric
PERM PERM Double 19 18 10 Numeric
COMP COMP Double 19 18 10 Numeric
FRACD FRACD Double 19 18 10 Numeric
MEAN_L MEAN_L Double 19 18 10 Numeric
MEAN_L95 MEAN_L95 Double 19 18 10 Numeric
MEAN_L05 MEAN_L05 Double 19 18 10 Numeric
Select All
Clear All
OK
Cancel
Apply

Method Overview

Segments Attributed with DEM morphology metrics → Automated decision tree classification algorithm → Final Classification Map

```
Decision tree:

MEAN_HS_1 <= 264.8669:
:...MEAN_HS_24 <= 1634.699: Residential Home (2)
:   MEAN_HS_24 > 1634.699:
:   :...PERC_L3 > 0.1471614: Trees (40/1)
:       PERC_L3 <= 0.1471614:
:       :...AREA <= 330: Trees (6)
:           AREA > 330:
:           :...SV_L_1 <= 0.2358841: Grass (12)
:               SV_L_1 > 0.2358841:
:               :...MEAN_L <= -22.07613: Trees (3)
:                   MEAN_L > -22.07613: Grass (3)
MEAN_HS_1 > 264.8669:
:...STDEV_L <= 0.2497618:
    :...MEAN_H_141 > 4324.309: Beach (2)
    :   MEAN_H_141 <= 4324.309:
    :   :...SV_L_12 <= 0.009653882: Water (39/1)
    :       SV_L_12 > 0.009653882: Road (2)
    STDEV_L > 0.2497618:
    :...MED_L > -22.33906:
        :...MAX_L <= -8.241442: Residential Home (32/2)
        :   MAX_L > -8.241442: Multi-Story Building (21)
        MED_L <= -22.33906:
        :...MEAN_HS_23 <= 330.9537: Water (3)
            MEAN_HS_23 > 330.9537:
            :...MED_L <= -24.75959: Road (17/3)
                MED_L > -24.75959:
                :...AREA > 1571: Parking Lot (15)
                    AREA <= 1571:
                    :...PERC_L8 <= 0.2424455: Multi-Story Building (3)
                        PERC_L8 > 0.2424455: Trees (3)


Evaluation on training data (203 cases):

          Decision Tree
        ----------------
        Size      Errors

          16    7( 3.4%)   <<


         (a)   (b)   (c)   (d)   (e)   (f)   (g)   (h)    <-classified as
        ----  ----  ----  ----  ----  ----  ----  ----
          16                                          1    (a): class Road
           2    15                                       (b): class Parking Lot
                      24     1                           (c): class Multi-Story Building
                           32     1                      (d): class Residential Home
                            1    51                      (e): class Trees
                                       15                 (f): class Grass
           1                                    2         (g): class Beach
                                                 41       (h): class Water
```

Why use a Automated Decision Tree Classifier?

- Large volume of data input
  - Inputs each have different distributions and characterizes that violate statistical assumptions.
  - Easy to interpret and understand what variables were utilized.
- Provides information on confidence of individual predictions
- Has been demonstrated as an effective tool in remote sensing classification in published research

Method Overview

Segments Attributed with DEM morphology metrics → Automated decision tree classification algorithm → Final Classification Map

Mean	15.8		21.1%					
SE	0.1		2.9%					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	<-classified as
	12	1		1				3	(a): class Road
	1	11	3	2					(b): class Parking Lot
			21	1	1		1	1	(c): class Multi-Story Building
				29	4				(d): class Residential Home
	1	1	1	3	41	5			(e): class Trees
					7	8			(f): class Grass
	1							2	(g): class Beach
	1				3			37	(h): class Water

Cross Validated Accuracy:
~ 80%

Problems:

- Shadows – Almost all shadowed area was misclassified
- Other smaller issues
  - Residential / Trees
  - Parking Lot / Open

Method Overview

Segments Attributed with DEM morphology metrics → Automated decision tree classification algorithm → Final Classification Map

Mean	15.8		21.1%						
SE	0.1		2.9%						
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	<-classified as
	12	1		1				3	(a): class Road
	1	11	3	2					(b): class Parking Lot
			21	1	1		1	1	(c): class Multi-Story Building
				29	4				(d): class Residential Home
	1	1	1	3	41	5			(e): class Trees
					7	8			(f): class Grass
	1							2	(g): class Beach
	1				3			37	(h): class Water

Cross Validated Accuracy:
~ 80%

Problems:

- Shadows – Almost all shadowed area was misclassified
- Other smaller issues
  - Residential / Trees
  - Parking Lot / Open

Method Overview

Inputs

Acquire Shoreline Data transformation (MLLW & MHW etc) from (NGS Gauge) and enter into textfile

DEM (Shoals Data)

Classification

Smoothing Parameter

Shoreline Delineation

Find closest gauge point to every cell in DEM & adjust values

Smooth Surface Using Low Pass Filter to remove “Stepping”

Replace Areas of No-Data using Filter

Create Contour at 0

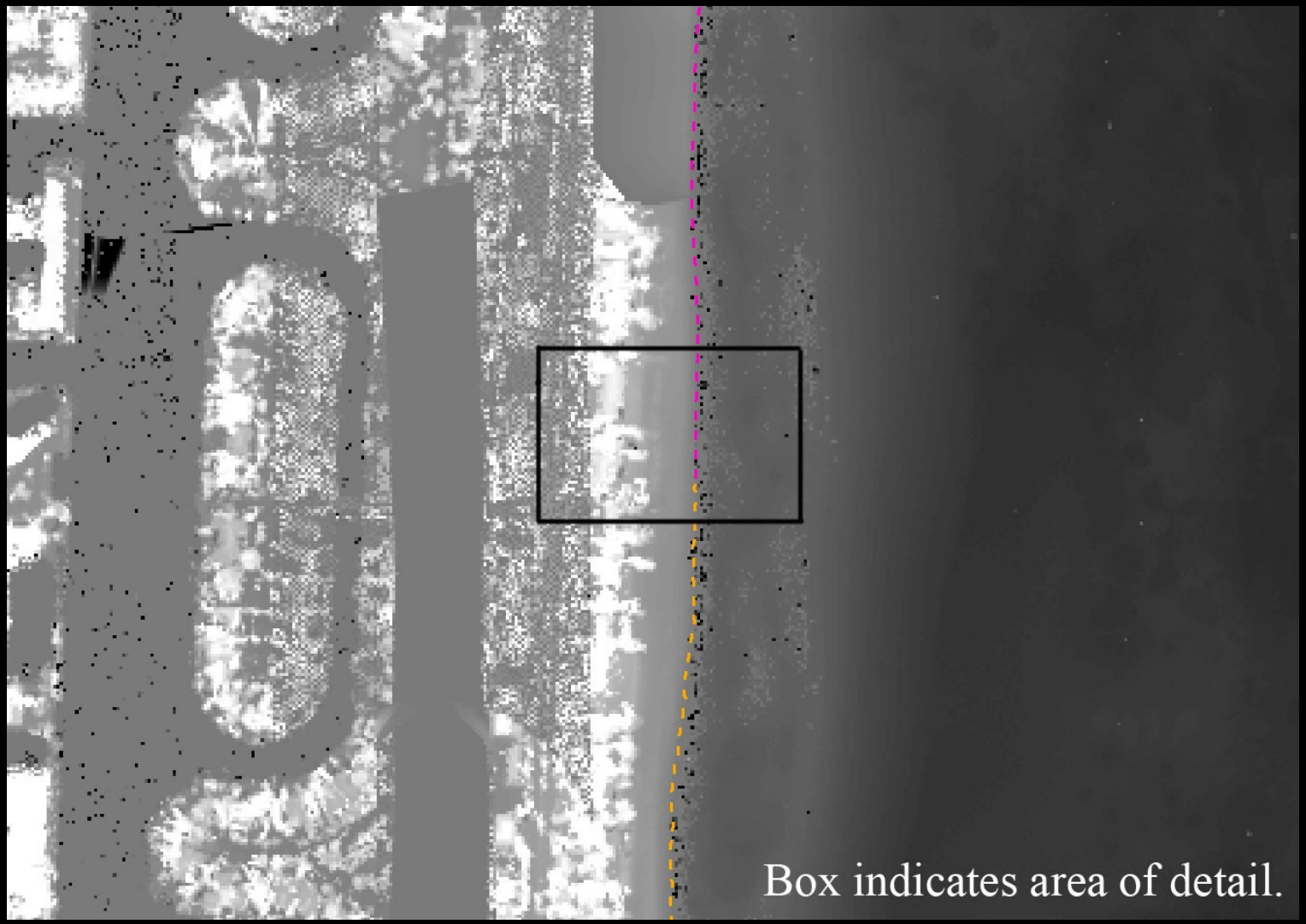
Smooth Shoreline using user input smoothing parameters

Re-break shoreline by class

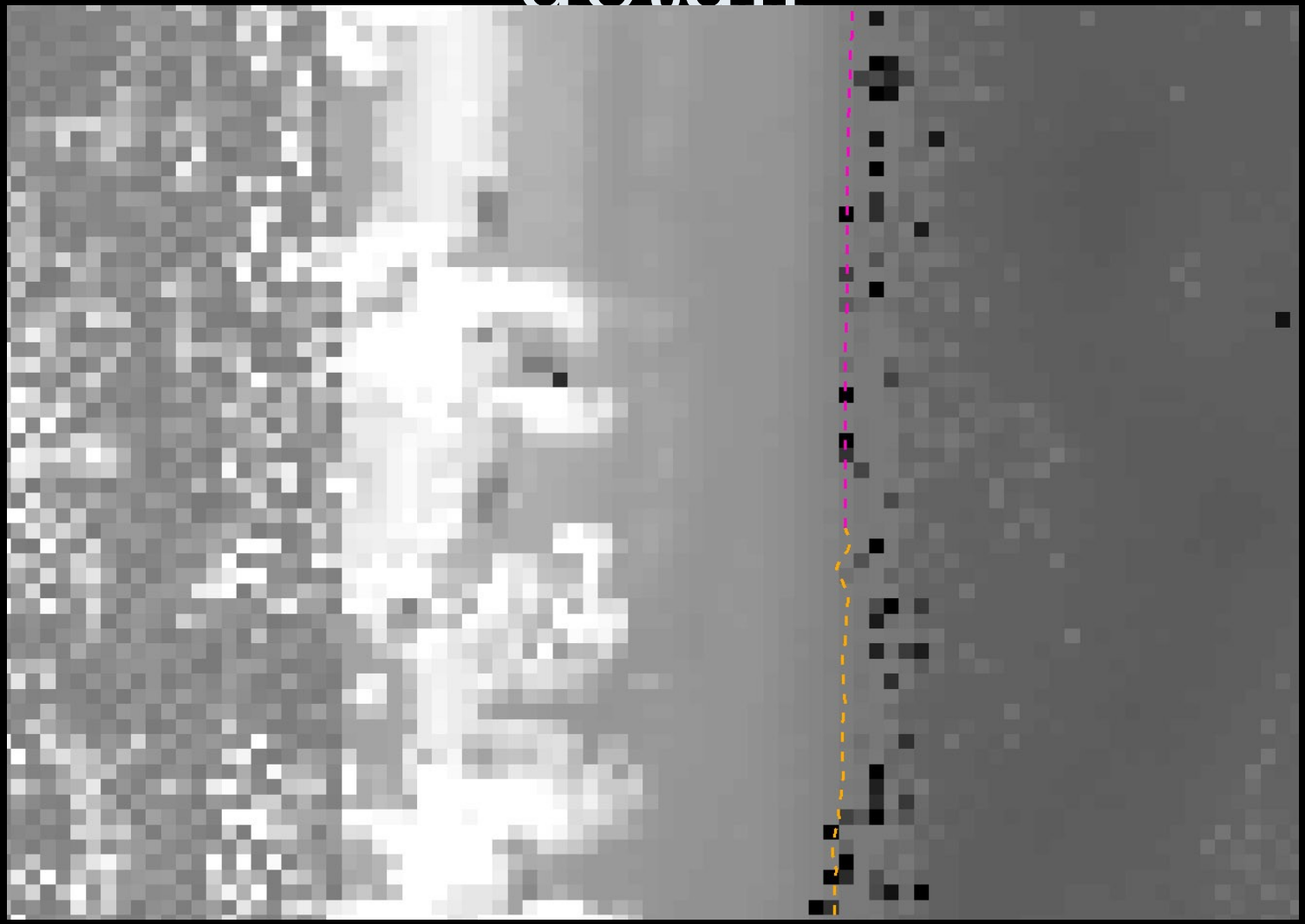
Output is an ESRI Shapefile

break shoreline by class

Test Results - Overview



Test Results – DEM detail



Test Results – Image detail

Future Work (Classification):

- Refine Algorithm
  - Include LIDAR in Segmentation process
  - Standardized Classification Scheme
    - Create Additional Classes
    - Shadow Classes?
  - Smooth / Filter Results
- To Code
  - Coupling / Recode Solution?

Future Work (Classification):

- To Code
  - Coupling / Recode Solution?
- Academic Pursuits
  - Present at ASPRS Conference
  - Work up draft research article on classification methodology

Future Work (Shoreline):

- Refine Algorithm
  - provide methods for dealing with inlets and other special areas
  - by testing the tool on other datasets with a greater variability in classes along the coast
- Enhance User Experience
  - Continue to work with end users (process has been initiated)
  - Provide intuitive input device (GUI) for input paramerts such as the IO datum / level of line smoothing
  - Provide a documented user help.